Multi-Label Classification of Learning Objects Using Clustering Algorithms Based on Feature Selection

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Abstract—In the field of online learning, the development of learning objects (LOs) has been increased. LOs promote reusing and referencing educational content in various learning environments. However, despite this progress, the lack of a conceptual model for sharing suitable LOs between learners makes multiple challenges. In this regard, multi-label classification plays a significant role to make high-quality LOs, which can be accessible and reusable. This article highlights a new way of using learning objects based on Multi-Label Classification (MLC) and clustering algorithms with feature selection techniques. It suggests a new system that makes the most suitable choice among many alternative sources based on the Sharable Content Object Reference Model (SCORM). The proposed algorithm has been tested on a real-world application dataset related to the data analysis service for the learning science community. The experimental results show that our algorithm outperforms the traditional approach and produces good results.

Keywords—E-learning systems, learning objects (LOs), Multi-Label Classification (MLC), feature selection techniques, clustering algorithms, Sharable Content Object Reference Model (SCORM)

1 Introduction

In the last 10 years, the research in E-learning on metadata of Learning Objects (LOs) has been significant [1]. There have been considerable efforts deployed by the IEEE Learning Technology Standards Committee (LTSC) and IMS Global Learning Consortium to develop and normalize a collective conceptual definition of Metadata elements in LOs [2]. Research in metadata elements of LOs brings a new vision of learning content. Traditionally, e-learning contents are not labeled by any metadata and consequently, they had not been stored and referenced in any e-learning environments. By definition metadata is data that describes other data, providing a structured reference that helps to sort and identify attributes of information it describes [3]. Metadata plays an essential role to represent and identify LOs. It is the key that lays the basis for classifying and sharing the LOs. Metadata involves double visions. On the one hand, a global comprehension of LOs, and on the other hand, it provides the opportunity to classify the LOs using classification algorithms in order to achieve a maximum rate of accessibility and interoperability. A classification approach can accelerate and establish efficiently the reusability of LOs in e-learning systems [4]. In this concern, our objective focused on developing a new approach for learning objects using Multi-Label Classification (MLC) based on clustering algorithms with feature selection techniques. Our approach suggests a new method that proposes the most suitable choice among many learning resources based on metadata clustering. Multi-label classification methods are needed in multiple applications such as music categorization, semantic classification of scenes, and classification of educational content in e-learning environments [5]. In all these applications, the objects to be classified can belong to more than one class. For example, one word can represent more than one concept. In the same way, several labels can be assigned and can be used to improve the experience of the studied object. Multi-label Classification (MLC) is an automatic process that uses analysis techniques in order to label an object and classify it by topic [6]. This approach used supervised learning where a feature may be connected with multiple labels. It is opposed to single-label classification when each feature is associated with a single class (label) [7]. Moreover, MLC is extensively applied in real-world problems, such as bioinformatics, e-commerce…etc. [8]. MLC plays an important role in the process of learning object classification due to its efficiency with the huge size of data and the difficulties of assigning a single label to each piece of content used in the courses. However, Few and insufficient studies have explored the MLC issue in the e-learning area. The typical goal of MLC in LOs classification is to construct a model in which labels are recommended for each feature in data and thus eliminate unimportant ones for time-consuming. This study proposes a generic approach for learning object classification using Multi-label Classification based clustering algorithms with feature selection techniques. This approach identifies each feature in metadata according to a particular form of similarity based on label correlation.

Feature selection, as a machine learning technique is used to find the best set of features that allows one to build useful models. The main role of feature selection in learning object classification is to identify pertinent features and eliminates redundant features from an excessive dimensional dataset [9]. We can adapt feature selection in several ways. Nevertheless, only three of them showed performance in the learning object classification: Filter based, wrapper-based, and embedded techniques. – The filter-based method [10] is based on statistical similarities algorithms that reduce the metadata to the most relevant features. – Wrapper-based measures [11] the "usefulness" of features based on the recursive feature elimination. – Embedded methods [12] combine the qualities of filter-based and wrapper methods. The objective of this article is twofold. First, it searches for the ability to construct a Multi-label Classification model for learning content via learning object classification. Second, it aims to suggest an enhanced version to create various high reductions based on clustering and feature selection. This paper is organized in this manner. Section 2 presents a thorough definition of the key concepts used in this article. Section 3 gives an overview of learning object Categorization with multi-label classification. The design of the approach used in this study is provided in section 4 with its different steps. Section 5 presents the experimental results. Finally, section 6 provides further directions to the multi-learning object classification problem using clustering based on feature selection.

2 Background knowledge

2.1 Learning Object

The success of an e-learning system is its capacity to recommend suitable learning objects based on the preferences of a specific learner. Learning object by definition is a new way to develop and reuse learning content; it aims to give labeled content for a specific lesson or subject in a large course [13]. Generally, the main characteristics of a learning object are Interoperability, Reusability, Manageability, Flexibility, and Accessibility. There have been considerable efforts deployed by the IEEE Learning Technology Standards Committee (LTSC) and the IMS Global Learning Consortium to normalize LOs and make them interoperable in diverse learning environments. The metadata that describes learning objects makes them more searchable and accessible to a wide audience.

2.2 Learning Object Metadata

Learning Object Metadata (LOM) standard as a concept has been published in 2002 [14]. It is used as a protocol of normalization for describing learning resources. The global aim of this standard is to provide access, reuse, evaluate, and facilitate the search for learning objects. LOM proposes a hierarchy of different metadata elements as shown in Figure 1, grouped into nine categories: General, Lifecycle, Meta-Metadata, Technical, Educational, Rights, Relation, Annotation, and classification [14].

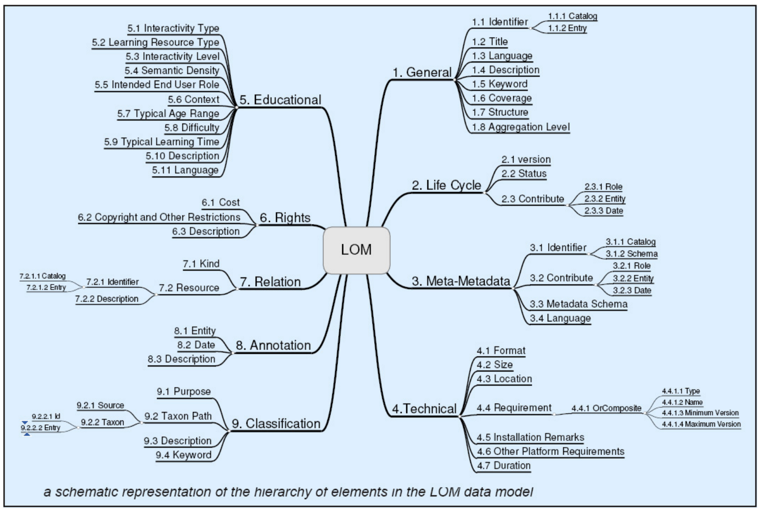

Fig. 1. A schematic representation of elements in the LOM data model ([14])

2.3 Multi-label classification (MLC)

Multi-label classification algorithms are mainly classified into lexicon approach and machine learning approach. In the Lexicon approach, each item is designated to a label based on a classification rule, which calculates the frequency of objects from the lexicons of each label. Machine learning techniques are divided as presented in Figure 2 into flat and hierarchical classifications. In flat classification, the set of labels is considered separately and classified in one level. Multi-label problem-based flat classification is divided into two techniques, which are problem transformation methods and algorithm adaptation techniques. The hierarchical multi-label issue is generally classified on tree-hierarchy or a directed acyclic graph (DAG) which are Homer [15], Hierarchical-KNN [16], and Hierarchical-DT [17].

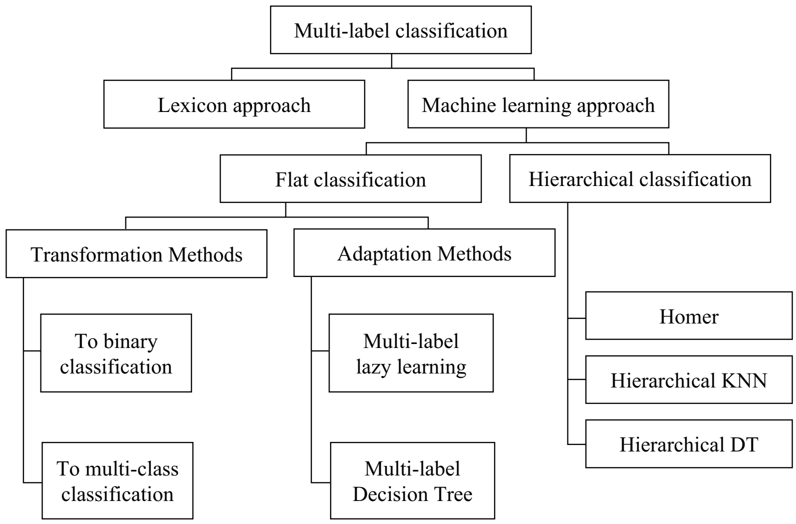

Fig. 2. Multi-label classification algorithms

2.4 Feature selection

Feature selection is one of the techniques used to reduce the dimensionality of data; it seeks to select a small subset of relevant features from the original set based on a relevance assessment criterion [18]. Feature selection can improve the performance of learning, for example, higher accuracy for classification. It can also reduce processing costs and enhance prediction accuracy.

Figure 3 shows a general feature selection for a classification framework.

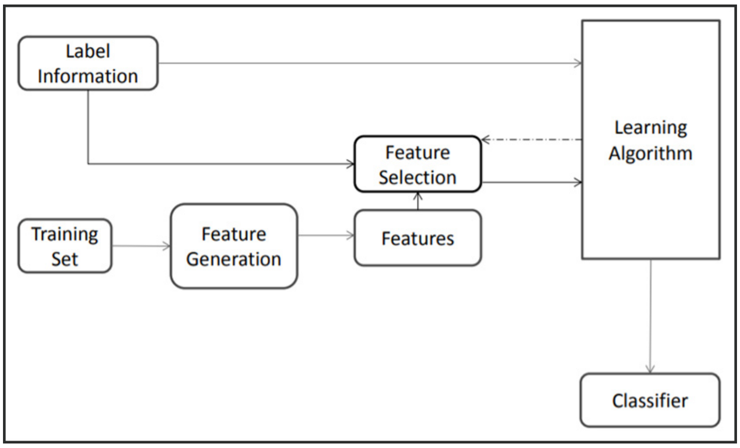

Fig. 3. A general framework of feature selection for classification

3 Multi-label classification algorithms for learning object classification

In the literature, a few studies have emerged multi-label classification paradigm and LOs in the e-learning approach. In these articles, diverse approaches have been recommended to incorporate feature-label selection into learning object content in order to enhance recommendation and accessibility [26]. These studies' focal point is on the manner to readjust formal single-label classifiers to stem multiple labels. Working on a model for multi-label classification and ranking of learning objects, the authors of [19] related the idea of searching LOs tagged by Learning Object Metadata (LOM), specifically the model offers a methodology that illustrates the task of multi-label mapping of LOs into type queries. In [20], the authors utilize a comparative evaluation of four multi-label classification algorithms in classifying learning objects. Therefore, the authors in [21] examine the hierarchical multi-label classification in the context of recommender systems. They suggest a hierarchical multi-label metadata classification with a machine-learning algorithm to improve the search and classification of educational content. Moreover, this research devotes itself to existing studies by presenting a hierarchical multi-label learning object of the dataset in a suitable format [24].

Table 1 presents a review of the significant research articles that have adopted MLC methods for learning object content using LOs metadata.

Table 1. Summary of the significant studies that applied MLC methods on the LOs

Reference	Year	MLC Type		Contribution
		Flat	HMC	
[19]	2011		√	A System for multi-label classification of learning objects.
[22]	2012			A model for multi-label classification and ranking of learning objects
[21]	2013			Multi-label classification for recommender systems
[23] [28]	2014			Evaluating the application of interactive classification system in university study course comparison
[20]	2016			Comparative evaluation of four multi-label classification algorithms in classifying learning objects
[25] [31]	2017	√		Towards automatic classification of learning objects: Reducing the number of used features
[27]	2018			Multi-label Green's Function Criterion inspired Transfer Annotation System
[29]	2020	√		Label Enhancement Manifold Learning Algorithm for Multi-label Image Classification

4 Methodology

This paper proposes a Multi-Label Classification for metadata LOs using clustering algorithms based on feature selection. Our objective in this study is to present a hybrid method (clustering algorithm—feature selection technique) tailored for learning object metadata classification problems. Our hybrid method is divided into two stages (see Figure 4). In the first stage, the clustering method classifies input data into a particular group with similar proprieties [30]. In the second phase, a feature selection technique assesses different feature subgroups formed by the clustering algorithm, determining the one that presents the best classification in terms of accuracy. The technique used in the clustering phase is a k-mean algorithm, and then we used embedded methods for feature selection that combine the qualities of filter-based and wrapper methods.

Algorithm 1 provides the main execution steps of our cluster based on the feature selection technique.

M_i represent a metadata and $LO\{lo_1, lo_2, lo_3, \ldots lo_n\}$ represent the set of n learning object. $W\{w_1, w_2, w_3, \ldots w_m\}$ describe the feature set of the LOs metadata.

Step 1: Normalization

This phase is particular to the metadata language content. It is concerned with replacing a specific alphabet with a normal one for example in French metadata we normalize abbreviations and shorthand forms used in the text.

Step 2: Removing Stop Word

It consists of removing all the non-significant words relating to the stop word list.

Step 3: clustering Algorithm

The distributional word clustering methods [6]–[18] calculate the distributions of words over classes, $P(c/w_j)$ $j \in [1,m]$ and p is the number of class labels, and use Kullback-Leibler divergence to measure the dissimilarity between two distributions. The distribution of a cluster w_j is calculated as follows:

$$P(C \setminus LOM_j) = \sum_{LOM_t \in LOM_j} \frac{P(LOM_t)}{\sum_{LOM_t \in LOM_j} P(LOM_t)} P(C \setminus LOM_t) \tag{1}$$

The goal of distributional word clustering is to minimize the following function:

$$\sum_{j=1}^{k} \sum_{LOM_t \in LOM_j} P(LOM_t) KL(P(C \setminus LOM_t), P(C \setminus LOM_j)) \tag{2}$$

which takes the sum of all the clusters.

Step 4: Feature Selection

For each learning object lo_i, $i \in [1,n]$, the feature reduction task tries to build a new set of words $LOM'\{LOM'_1, LOM'_2, LOM'_3, \ldots LOM'_k\}$ $k \le m$, in which After feature reduction, each learning object lo_i, is converted to a new representation lo'_j.

Where M matrix covers the entire original lo_i, with m features, and M' matrix comprises the converted metadata with new k features. The new feature set $LOM'\{LOM'_1, LOM'_2, LOM'_3, \ldots LOM'_k\}$ corresponds to a partition of $LOM\{LOM_1, LOM_2, LOM_3, \ldots LOM_m\}$. The jth feature value of converted document d'j is calculated as follows:

$$lOM'_{ij} = \sum_i LOM_t \in LOM_j lo_{it} \tag{3}$$

Step 5: Evaluating the Performance

The performance of the result is compared with an existing algorithm based on parameters like precisions, recall, and F-Measure.

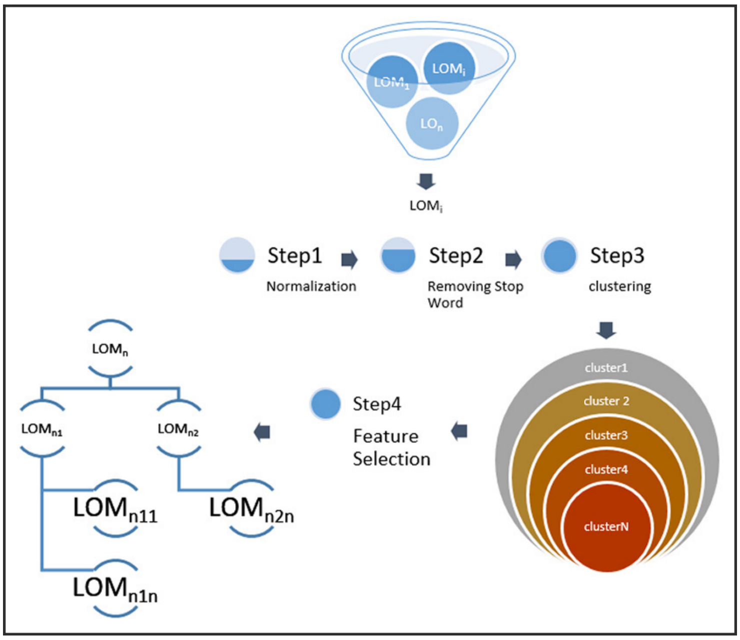

Fig. 4. Our approach of multi-label learning object classification using clustering algorithms based on feature selection

5 Experimental results

This section presents the results of experiments on learning objects classification using statistical methodology.

5.1 Dataset analysis

Our corpus (see Tables 2–5) is collected from four existing corpora on the official website DataShop of a data analysis service for the learning science community, which provides two main services to the learning science community:

- A source to store research data
- A regular set of examination and reporting tools

In public datasets proposed by the DataShop website, we have chosen four datasets, which are Digital Games for Improving Number Sense by Derek Lomas, EDM Summer School 2017 by John Stamper, French Course by Christopher Jones, and Fractions Lab Experiment 2012 by Vincent Aleven. All these datasets have description metadata. Our objective is to explore their metadata with our algorithms in order to compare the effect or not of our proposed approach. For the experience, we have integrated all these datasets in different e-learning environments and we have used our classification algorithms for all LOs composed in this dataset. The experimental period has been fixed from

01 January 2020 to 31 December 2020. The tables below present more details about the initial number of transactions of the chosen dataset.

Table 2. Fractions lab experiment 2012 by: Vincent Aleven

Dataset	Area/Subject	Date	Status	Transactions
FractionStudy2012	Math/Other	Oct 10, 2012–Jun 15, 2020	Complete/with metadata	228347
Lab study 2012	Math/Other	Oct 20, 2012–Apr 7, 2013	Complete/with metadata	37889
Classroom study 2013	Math/Other	May 14, 2013–May 15, 2013	Complete/with metadata	42687
Non-numeric	Math/Other	May 23, 2013–May 23, 2013	Complete/with metadata	33609
Classroom study 2013	Math/Other	May 14, 2013–May 15, 2013	Complete/with metadata	42687

Table 3. French course by: Christopher Jones

Dataset	Area/Subject	Date	Status	Transactions
FrenchLanguage	Language/French	Aug 25, 2006–Jan 15, 2010	Complete/with metadata	436,493
FrenchLanguage2	Language/French	Jan 2, 2007–Apr 10, 2010	Complete/with metadata	71,553
FrenchLanguage2	Language/French	Jan 10, 2007–Jan 31, 2007	Complete/with metadata	183
Pitteiffel	Language/French	Sep 29, 2007–Dec 13, 2007	Complete/with metadata	1,124
Toureiffel	Language/French	Sep 29, 2007–Dec 11, 2007	Complete/with metadata	1,124

Table 4. EDM summer school 2017 by: John Stamper

Dataset	Area/Subject	Date	Status	Transactions
Geometry Area (1996–97) [2017 Summer School]	Math/Geometry	Feb 1, 1996–Feb 1, 1996	Complete/with metadata	6,778

Table 5. Digital games for improving number sense by: Derek Lomas

Dataset	Area/Subject	Date	Status	Transactions
Digital Games for Improving Number Sense – Study 1	Math/Other	Feb 24, 2011–Mar 5, 2011	Complete/with metadata	4,391

5.2 Classifier accuracy

We implemented our proposition described above and tested the performance of the Metadata classification on all datasets. For each LOs, we obtain a number of consultations and downloads by month. Table 6 gives the corresponding values from the log file.

Table 6. Micro precision, recall and F1 of MLTC algorithms

Month	Fraction_ Study 2012	Geometry_ Area	Lab_ Study_ 2012	Classroom_ Study 2013	French_ Language	Tour_ Eiffel	Digital_ Games_for_ Improving_ Number_ Sense
January	245	167	123	234	154	15	432
February	143	223	82	321	129	5	345
March	321	189	106	98	178	97	498
April	123	321	79	126	118	34	343
May	456	193	271	231	76	121	768
June	287	194	178	267	192	61	456
July	789	545	467	421	334	125	897
August	1098	875	678	767	583	345	765
September	897	1298	567	1457	678	734	1134
October	2173	1689	772	1870	1459	897	973
November	1590	1563	678	1456	1671	1256	1783
December	1762	2564	1432	2135	2867	1567	1286

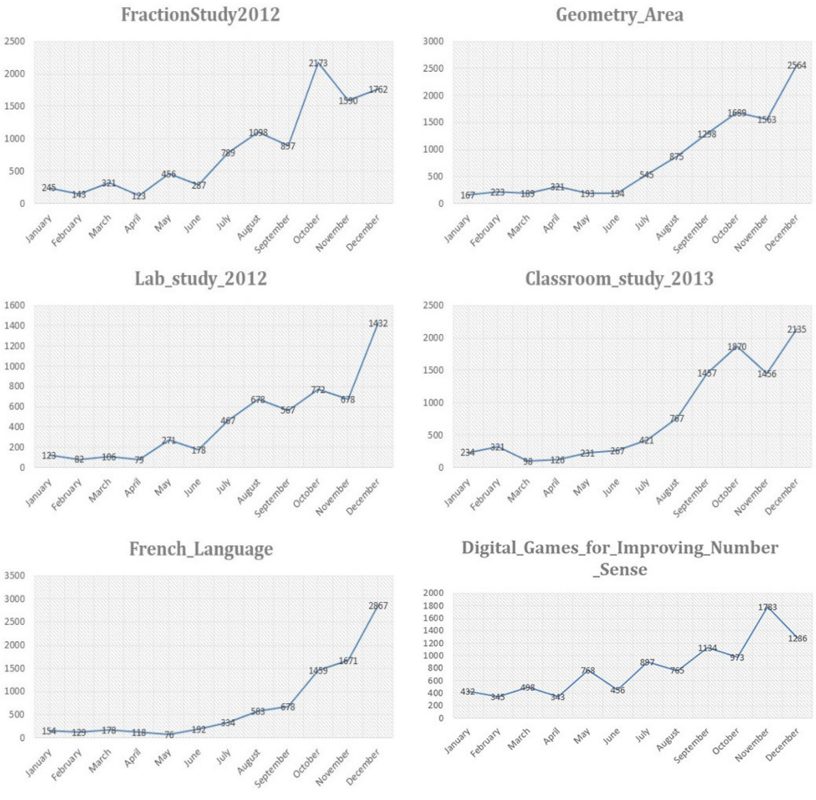

Fig. 5. Number of consultations by month for each LO between 1st January and 31st December 2020

The results showed in Table 6 and Figure 5 disclose that our approach enhances consultation and improves the quality of document recommendations. From the obtained results, we can see that in the last 6 month the number of consultations by learners has significantly increased for all LOs, which explain that our approach makes the LOs more visible and reusable.

6 Conclusion

This study has approached the problem of metadata classification for LOs elements. It has introduced a novel approach using a clustering algorithm with feature selection techniques. This approach classifies each LO in data according to a particular form of similarity based on metadata label correlation. The results of this study have shown that the suggested method increases the suggestions and recommendations of educational content with a multi-label classification of LOM.

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